*Prediction of S-Wave Velocity using Machine Learning Algorithms Combined with Empirical Mode Decomposition-Based Approaches

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Abstract

The P- and S-wave velocities (Vp and Vs) are keys parameters in reservoir characterization workflows.

In contrast with Vp measurements, Vs logs are less available at all the well locations. Therefore, they are estimated from Vp using different approaches and formulae. Due to their non-stationarity and non-linearity , the conventional methods don't often lead to accurate estimations.

Here, we present a new method to predict Vs log from Vp log using a supervised machine learning model, namely multiple layer perceptron artificial neural network (MLP ANN). The ouput is the forecasted Vs values at different depths, while the inputs are composed of five logs: Vp log, its associated regularity Hölderian (Hp) log , and the three components (the high frequency-HF-, the low frequency-LF- and the trend) derived by combining different decomposition techniques (empirical mode decomposition –EMD-, ensemble empirical mode decomposition-EEMD-, and complete ensemble empirical mode decomposition-CEEMD) with the Hölderian regularity-based fine-to-coarse reconstruction (HR-FCR) algorithm.

Different MLP ANN inputs have been considered. Our finding shows that the most accurate predicted Vs values are obtained using the following inputs: P-wave velocity log, its Hölderian regularity log, and the three components (HF, LF and trend) obtained by CEEMD and HR-FCR algorithm. To conclude, the suggested approach might be efficient to estimate S-wave velocity in complex geological settings.

Keywords: S-wave velocity, EMD, EEMD, CEEMD, Hölderian regularity, multilayer perceptron neural networks (MLP ANN).

Extended Abstract

P- and S-wave velocity (Vp & Vs) bring manyuseful information to petroleum exploration. Since Vs is often not measuered at well locations, it is estimated from Vp using different empirical linear models which fail to deal with the non-linear features inherent to the geology (Pickett, 1963; Castagna et al., 1985; Han, 1986; Mavko et al., 1998).

The advent of intelligent systems made spatial modeling and prediction of physical properties very successful . Amongst these techniques, multiple layer perceptron artificial neural networks (MLP ANNs). MLP ANNs have been fruitfully used for predicting lithofacies from well logs data (Frayssinet et al., 2000; Goutorbe et al., 2006, Farfour et al., 2012).

Here, the MLP ANNs are used to predict Vs log from Vp log using inputs resulting from the original dataset. Four (04) inputs have been considered: the original Vp log, and its corresponding pseudo-logs: local fractal (or Hölderian regularity) log (Hp), and the three components (high frequency-HF-, low frequency-LF- and trend) (Gaci, 2017).

Three (03) situations have been considered for the estimation of HF, LF and trend components. These components have been computed using the empirical mode decomposition (EMD), the ensemble empircal mode decomposition (EEMD), and the complete ensemble empircal mode decomposition (CEEMD) (Gaci and Farfour, 2021).

The suggested approach has been implemented on P- and S-wave velocity logs measured at the pilot and main boreholes (in short, VB and HB respectively), dilled during the German Continental Deep Drilling Program (KTB) (Figure 1).

For the puropose of comparing the prediction of Vs from Vp log data using the three studied cases, the mean square error (MSE) has been considered. The obtained MSE values expressed in $(m/s)^2$, corresponding to the cases: 1 (EMD), 2 (EEMD), and 3 (CEEMD) are 56749, 83765, and 46749, respectively. These results demonstrate the more accurate presdiction of Vs from Vp data is reached using CEEMD.

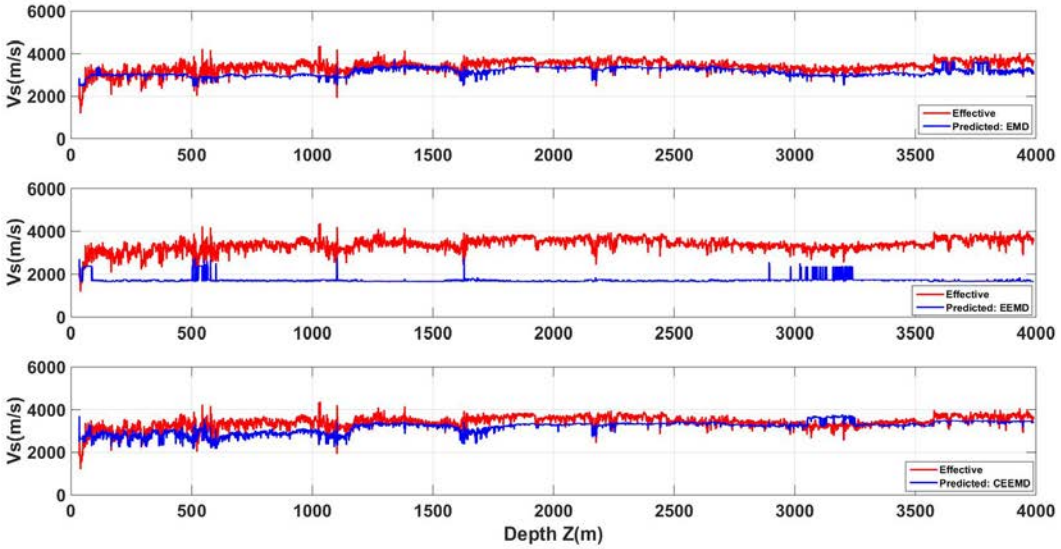

Figure 1. Estimations of S-seismic wave velocity (Vs) log at well KTB-VB using the dataset related to well KTB-HB corresponding to the three considered cases. In blue: MLP ANN predicted Vs; in red: effective Vs log recorded at well KTB-VB.

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